Comparing Learning Strategies for Topographic Object Classification

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***Abstract*— Two methods of topographic object classification through shape are described. Unsupervised classification through clustering analysis is compared with supervised classification based on a Bayesian framework. Both are applied to the real world problem of checking and assigning feature-codes in large-scale topographic data for use in computer cartography and Geographical Information Systems (GIS). Categorisation is accompanied by a confidence measure that the classification is correct. Both types of classification were implemented and their outcomes evaluated and compared. As a case study, results and conclusions are presented on the classification and identification of archaeological feature shapes on OS large-scale maps. It was found that the supervised classification model used out-performed the unsupervised classification model to a considerable degree.**

Keywords- topographic object classification; learning strategies; fitting distribution models

I. INTRODUCTION

For many of the applications used in computer cartography or in Geographic Information Systems (GIS), topographic data has to be structured according to the semantic, as well as geometric, information it indicates. That is, the objects depicted by the data have to be attributed with labels or codes indicating the real-world objects they depict. For example, objects may be separated into classes representing buildings, roads, rivers and so on. Data providers often have a standard ontology (set of classes) that they use in data sets. For their particular application, users may need an alternative or more detailed classification.

Whereas the geometry of topographic maps is often captured automatically through scanning and vectorisation, or semi-automatically from imagery, encoding the semantic component is usually a manual process. This can be a time-consuming process and so any progress in automation is to be welcomed. Attempts have involved techniques relying on object shape [3, 6], object structure [7] and context [8]. Methods depending on object shape usually produce descriptors, modeled by a set of real numbers, that uniquely characterize each object. The objects class can be identified by comparing it to standard descriptors for each object class.

II. OBJECT CLASSIFICATION: SUPERVISED VERSUS UNSUPERVISED METHODS

There are two general forms of classification possible: unsupervised and supervised. Unsupervised learning occurs where the distribution of descriptor values of objects in a data set is analysed. Clusters of objects of similar shape are assumed to represent a class. Supervised learning occurs when the classes to which objects are to be assigned are decided beforehand. Values of descriptors that characterise each object class are determined and objects are classified through the similarity of their descriptors to these characteristic values.

A. *Clustering Model*

Unsupervised classification (or clustering) locates a pre-selected number of cluster centres in the n-dimensional space and proceeds to redefine clusters iteratively until they have achieved maximum statistical separation. An algorithm is used to partition the distribution of a set of shape descriptors. In order to carry out the classification K-means (partitional clustering), linkage hierarchical clustering algorithms are applied [1,4,5].

B. *Bayesian Learning Model*

Supervised classification [1,5] is performed using Bayes theorem. Supervised learning occurs when the classes to which objects are to be assigned are decided beforehand. Values of descriptors that characterise each object class are determined in some way and objects are classified through similarity or their descriptors to these characteristic values. So supervised classification involves two stages: a learning stage where criteria and methods are tried on the prototypes and recognition when the trained system is used to classify new data. In this work we are using supervised classification through Bayesian statistics. The set of shape functions from all classes is used to derive maximum likelihood estimation for an unclassified shape.

III. DIFFICULTIES IN CLASSIFICATION

Classification can be heavily dependant on the type of data used by the system. The issues raised with regard to classification for map data categorisation are:

- how the choice of methods affect performance;

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- how the data used affects the performance of the classification algorithms and
- how each type of learning performs given the type and nature of the data being examined (topographic data).

IV. TOPOGRAPHIC OBJECT CLASSIFICATION

The overall goal and aspiration of this research work is the design and implementation of an expert system to automatically structure and recognise graphical data [3,6]. Automatically structuring of topographic data for use in a GIS application is one aspect of this.

GIS is used as the main tool for the analysis and processing of spatial data. This data is stored in digital form as points, lines and polygons much like traditional paper maps. However, to automate many tasks, the data has to be structured explicitly with information and relationships only implied by the paper version. In an object model, for example, a building is represented as a unique identifiable object containing not only the geometry that depicts it but also attribute information describing non-geometric features (for example, the address). For a particular task, the user might attach specific information to the basic structuring provided on the digital map.

The work involved in the conversion of large data-sets into an object model is considerable. Therefore, it is very labour intensive to structure the data manually. Some automation of this process is possible. Previous work has tackled this problem through shape recognition and context analysis of map features. These methods only deal with the classification of simple object types e.g. buildings, roads, etc. Many map features, however, can be considered more complex. For example, a university campus as depicted on a large-scale map, consists of numerous buildings, walls, paths and so on. So the campus is not any particular object but a composite of many other simpler objects. These may themselves be composite objects. This hierarchical structure applies to many kinds of object that map users are interested in (for example, industrial complexes, parks, government facilities, and leisure complexes). A further example is archaeological and other heritage sites [2].

V. CASE STUDY: ARCHAEOLOGICAL FEATURES

In the current data structure, archaeological features are represented as line features and text points. Depicting heritage features in this way means that there is no logical connection between the text (heritage text) and the actual line features (for example, slopes) representing it. One way to represent these archaeological features in a truly object oriented (OO) cartographic database requires that they be grouped into a hierarchical structure.

To group the archaeological (heritage) features in this way, they need to be identified and extracted from the data set. This can be achieved by searching the data-sets for likely archaeological features and confirming their status as such and also ascertaining their extent by distinguishing between features that do and do not belong to the site. Then, by creating a bounding polygon using either existing geometry and/or new lines, a composite model can be modelled to include the relevant features and geometry.

A typical archaeological feature is depicted in figure 1. In recognizing its constituent parts complications will arise because the areas representing slopes (shown in figure 1 by hachures) may also represent modern man-made features such as embankments or road cuttings. Therefore it is important to distinguish the actual archaeological features from other anthropogenic forms. Previous work on shape recognition techniques is applied to distinguish the actual archaeological features from other man-made forms. This paper is concerned with the classification confidence and any misclassifications arising from the feature recognition process. Also we empirically examine and ascertain how classification through clustering performs in comparison with supervised learning given the type and nature of the data being identified.

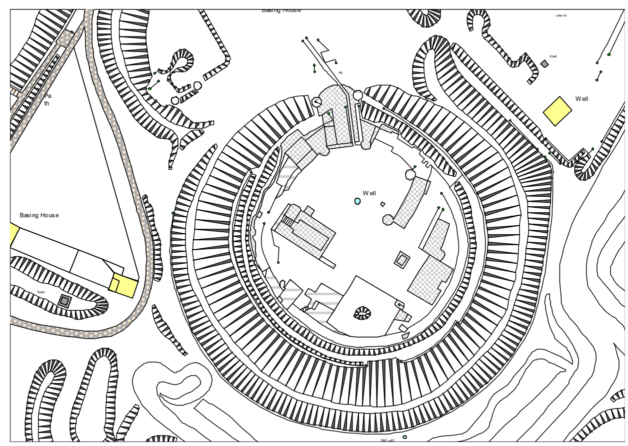

Figure 1. Archaeological site as depicted on a 1:2500 OS plan

VI. EXPERIMENTAL RESULTS

The following section outlines the empirical results obtained for the identification and classification of heritage features on OS MasterMap data. The objects to be classified are extracted from the map. The boundary of each sloping feature is used in the analysis and classification process for the discrimination of the heritage features from the modern features.

Results showed that both partitional and hierarchical unsupervised classification methods were unable to give us a successful classification of the data (Table II). The K-means method produced misclassification rates in the range of 50%-80% while the hierarchical methods presented misclassification of over 80%. This is due to the natural overlap that occurs within the data used (heritage and modern). In general, for graphical object recognition, some of the objects to be identified can be described as being *semantically similar*, that is though visually human perception can recognise an object (for example, a building) from its shape, the actual shape depicting each object feature may vary considerably. In this instance, natural overlap between the classes occurs which affects the performance of the clustering algorithms.

TABLE I. CORRECT CLASSIFICATION RATES FOR SUPERVISED LEARNING USING BAYESIAN MAXIMUJ LIKELYHOOD CLASSIFIER.

Descriptor	%Heritage	%Modern
Fouriers	100	90
Scalars	60	100
Moments	100	90

Table I shows the results obtained by three shape techniques, Fourier Descriptors, Moment Invariants and Scalar Descriptors, used for the shape discrimination of the heritage features from modern features. In this case Maximum Likelihood Classification (MLC) is used.

TABLE II. CORRECT CLASSIFICATION RATES FOR UNSUPERVISED LEARNING USING VARIOUS CLUSTERING METHODS.

Descriptor		%Heritage	%Modern
Fouriers	*K-means*	20	100
	Fuzzy K-means	20	100
	Single Linkage	100	0
	Complete Linkage	100	0
	Centroid Linkage	100	0
	Maximum Likelihood	100	90
Scalars	*K-means*	17	100
	Fuzzy K-means	18	100
	Single Linkage	100	0
	Complete Linkage	100	0
	Centroid Linkage	100	0
	Maximum Likelihood	60	100
Moments	*K-means*	50	100
	Fuzzy K-means	50	100
	Single Linkage	100	0
	Complete Linkage	100	0
	Centroid Linkage	100	0
	Maximum Likelihood	100	90

Comparing the performance of supervised classification against unsupervised classification showed that the supervised classification (maximum likelihood classifier) outperformed each of the unsupervised techniques. Of the partitional classification algorithms, *k-means* (also fuzzy k-means) performed reasonably well in comparison to the maximum likelihood classifier but produced a larger set of misclassifications. By far the most disappointing methods implemented were the hierarchical clustering techniques, which provided poor classification of the data in comparison to the k-means, fuzzy k-means, and maximum likelihood classifier.

VII. DISCUSSION

Supervised learning proved the most successful technique for the classification of topographic data (and, particular, for the archaeological features used here). However, in the classification a normal distribution of descriptor values was assumed. A refinement of this method uses curve fitting to more accurately characterise the distribution of the shape function.

To optimise classification performance it is important to obtain a good statistical model of the data under study. With Bayesian statistics, if this model (that is, the conditional density function) is not available it can be estimated. Knowledge of the density function associated with the training data is essential and enough for the complete characterisation of the statistical behaviour of the data under study.

Future work will derive a probability distribution function from model fitting the distribution of shape descriptors obtained for different types of topographic object classes (simple and complex objects). Supervised classification through Bayesian statistics will be implemented using the derived shape distribution function.

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